Can CERES help constrain the cloud feedback?

Stephen Po-Chedley and Nick Siler

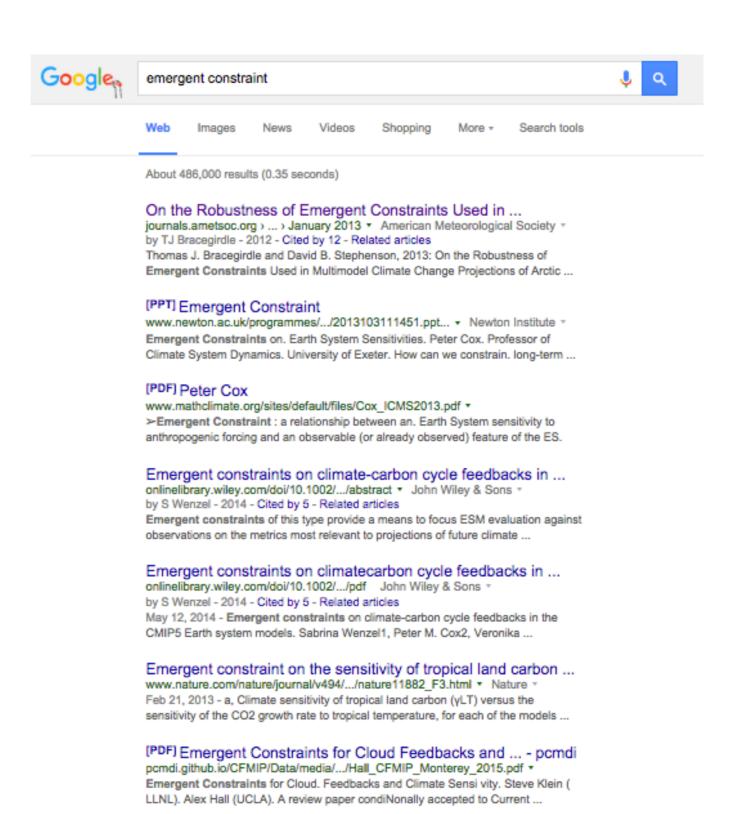
CERES Science Team Meeting University of Washington

September 2, 2015

Outline

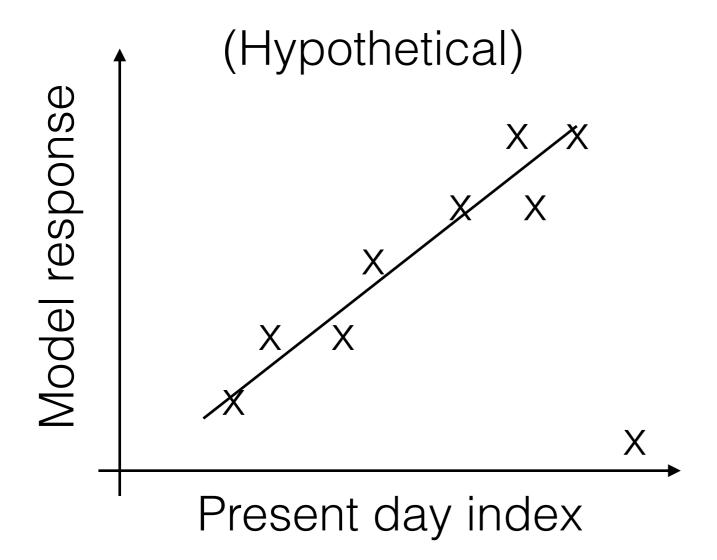
Constraint from SW CRE O Comments O O O Summary

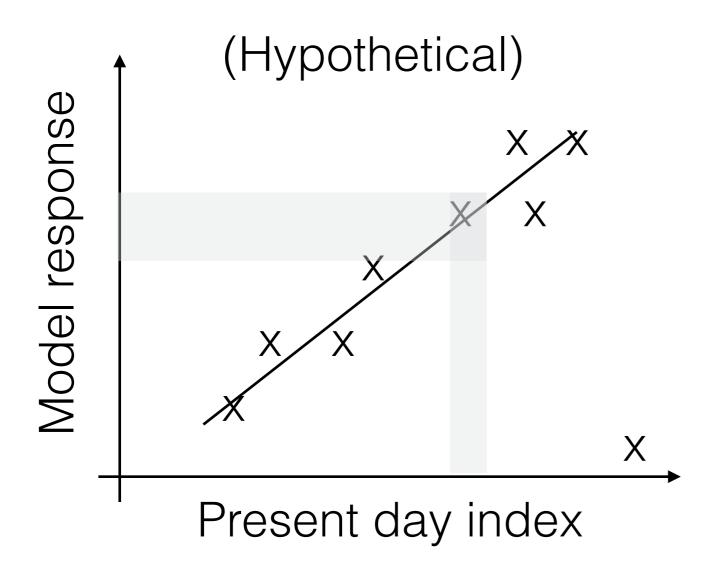
Emergent constraintsOOOOOO OOOO OOOO



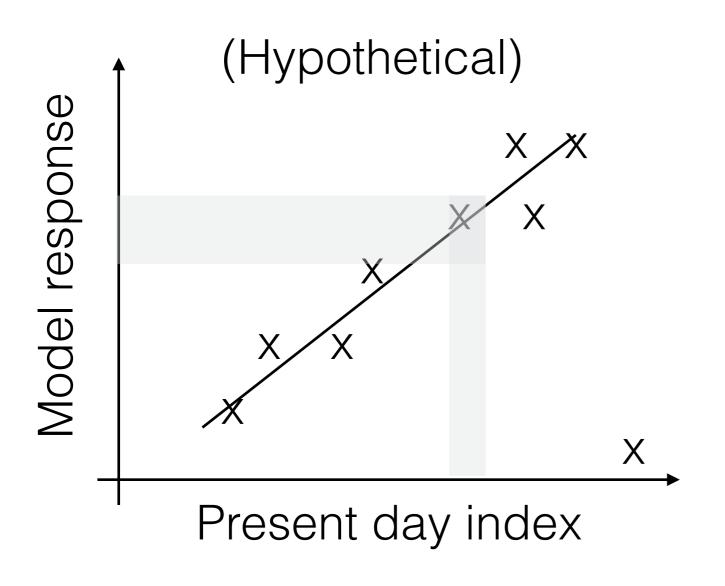
(PDF) simple test of cloud based emergent constraints for ... - p...

ocmdi.github.io/CFMIP/Data/media/2015/wagman_CFMIP_2015.pdf +

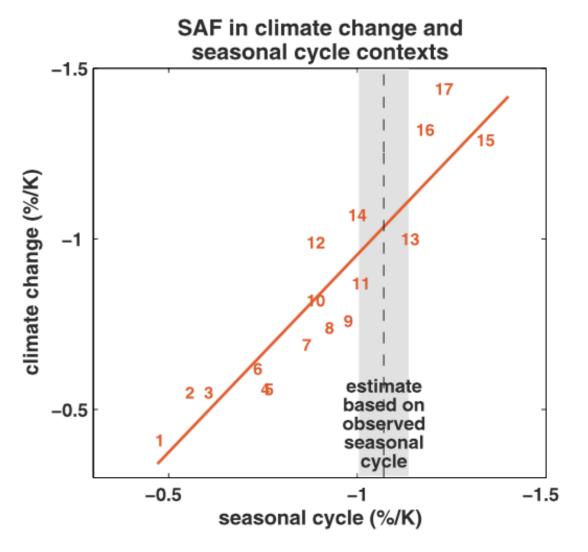


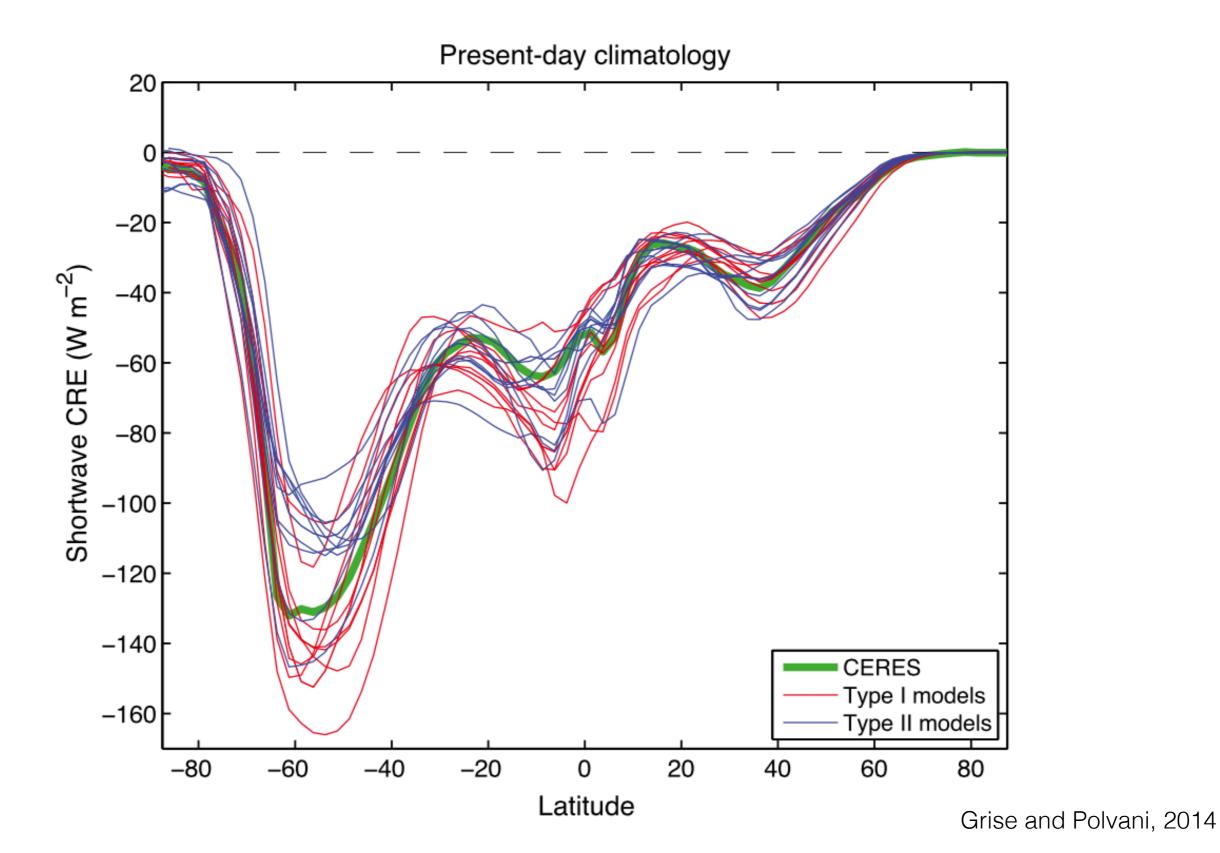


Emergent constraints 0000000 0000 0000 0



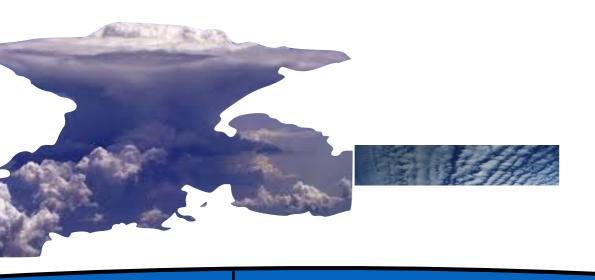
Snow albedo feedback



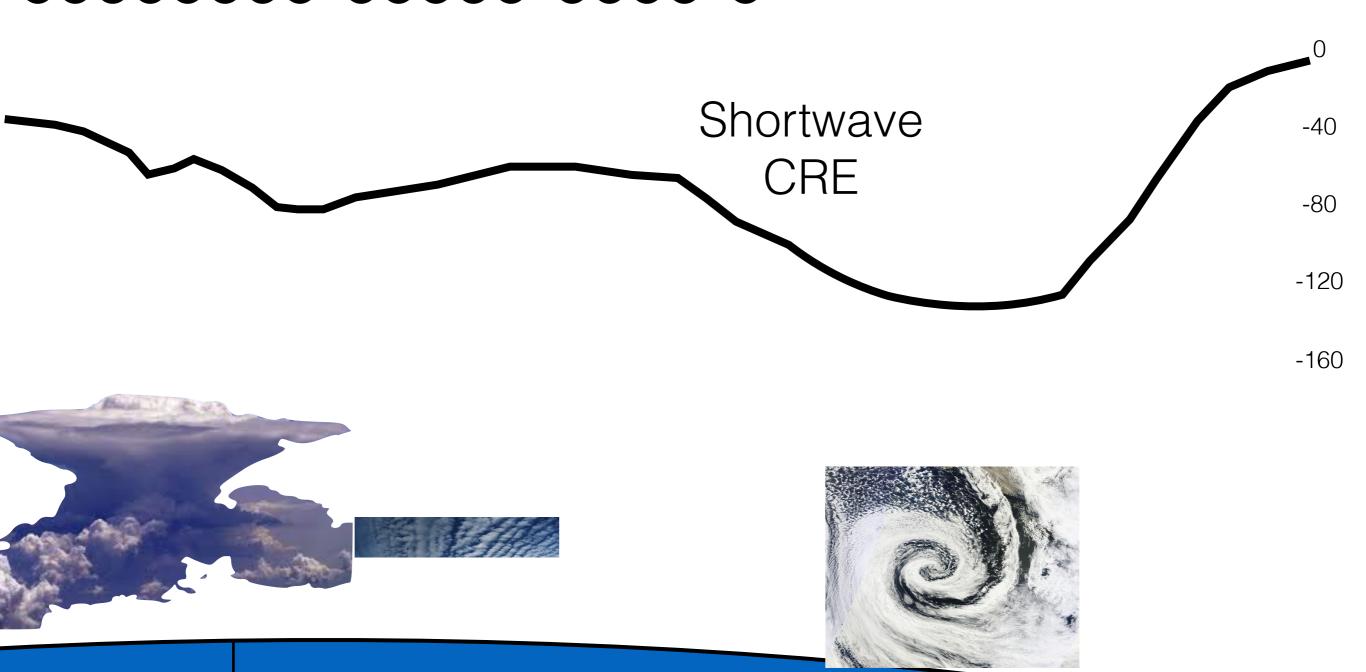




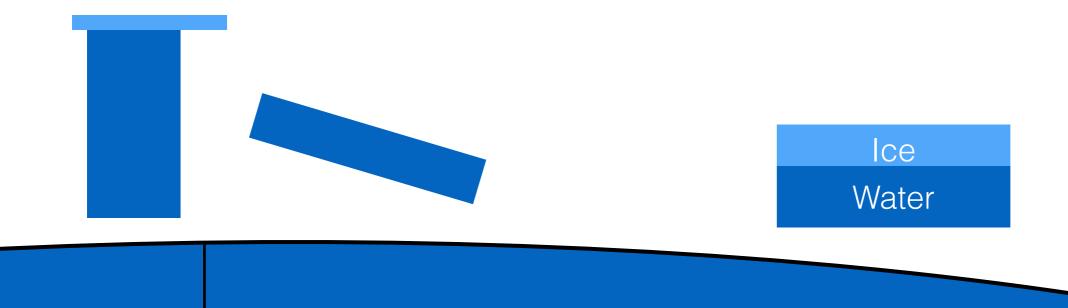


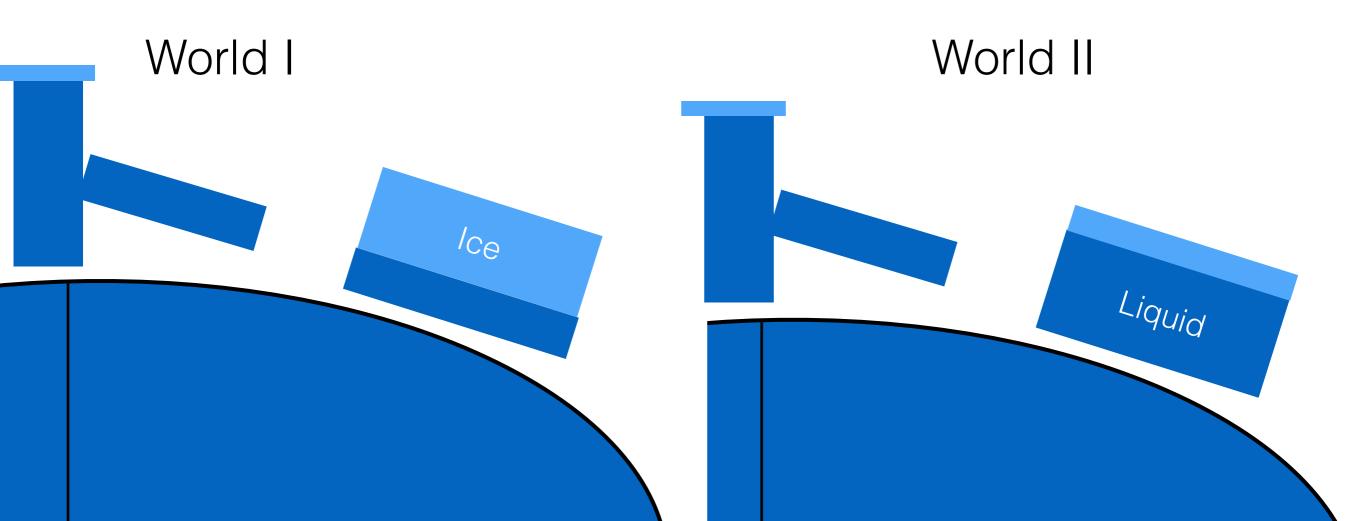


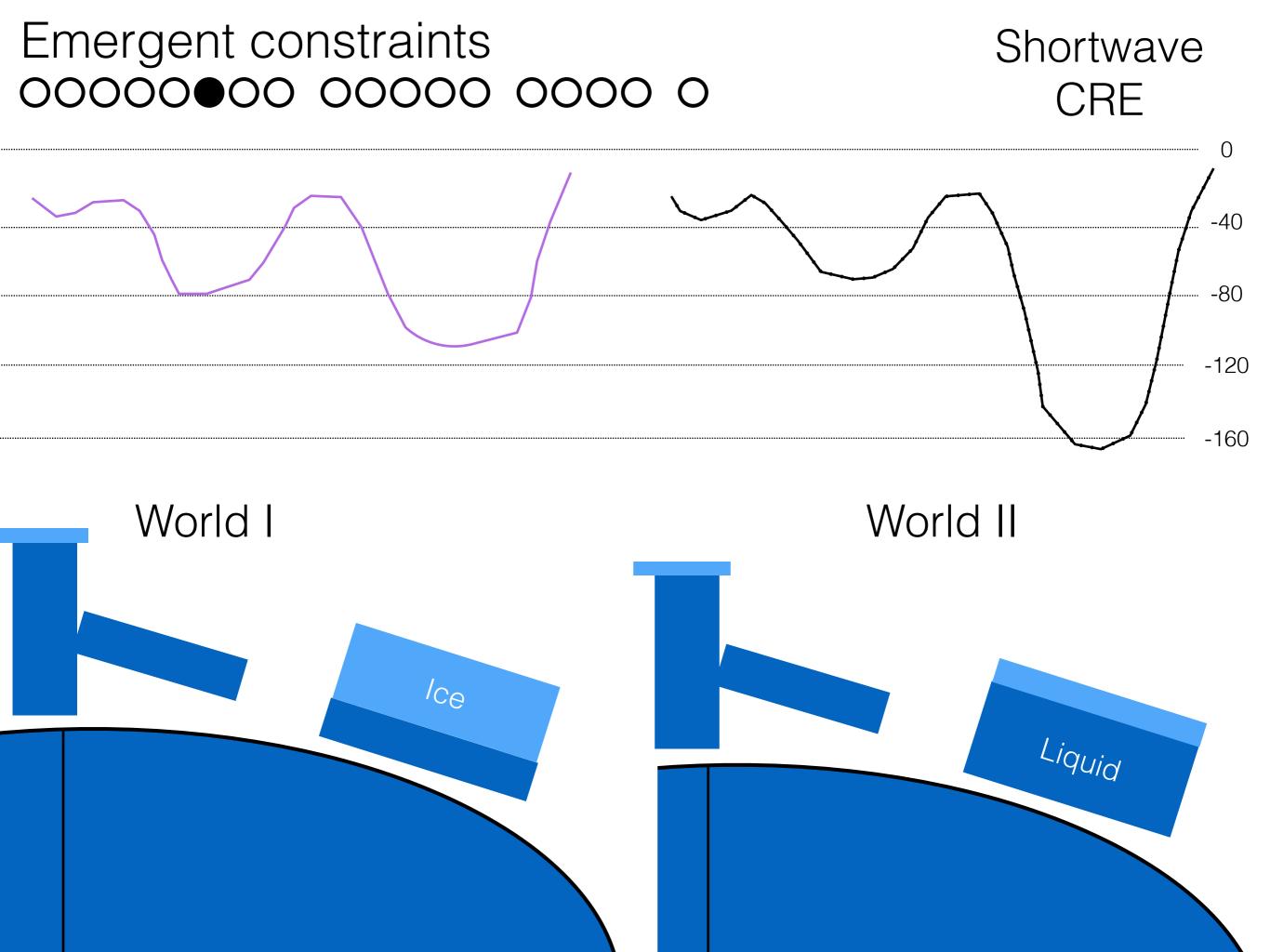


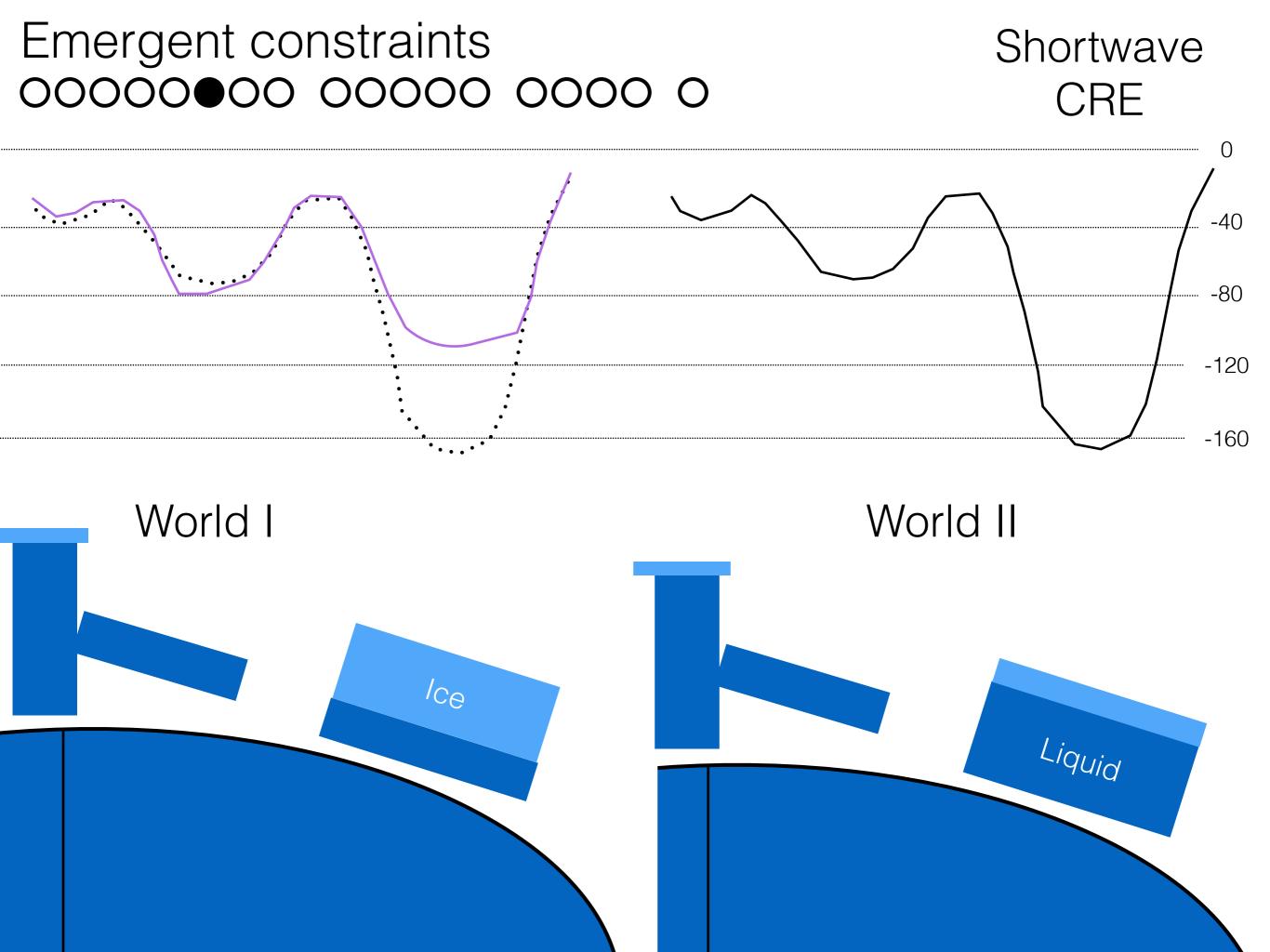


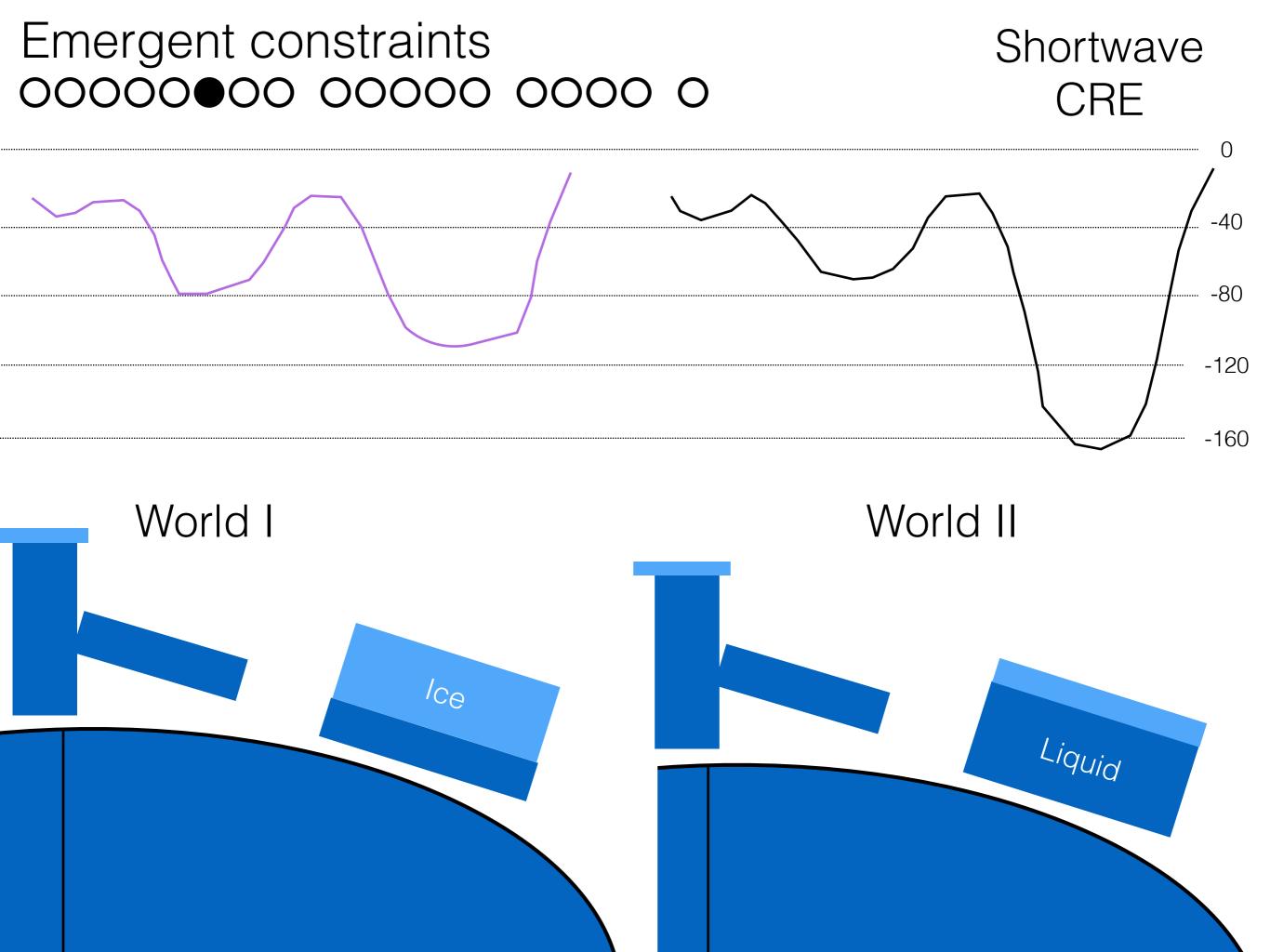
Emergent constraints 0000 000 0000 0000 0

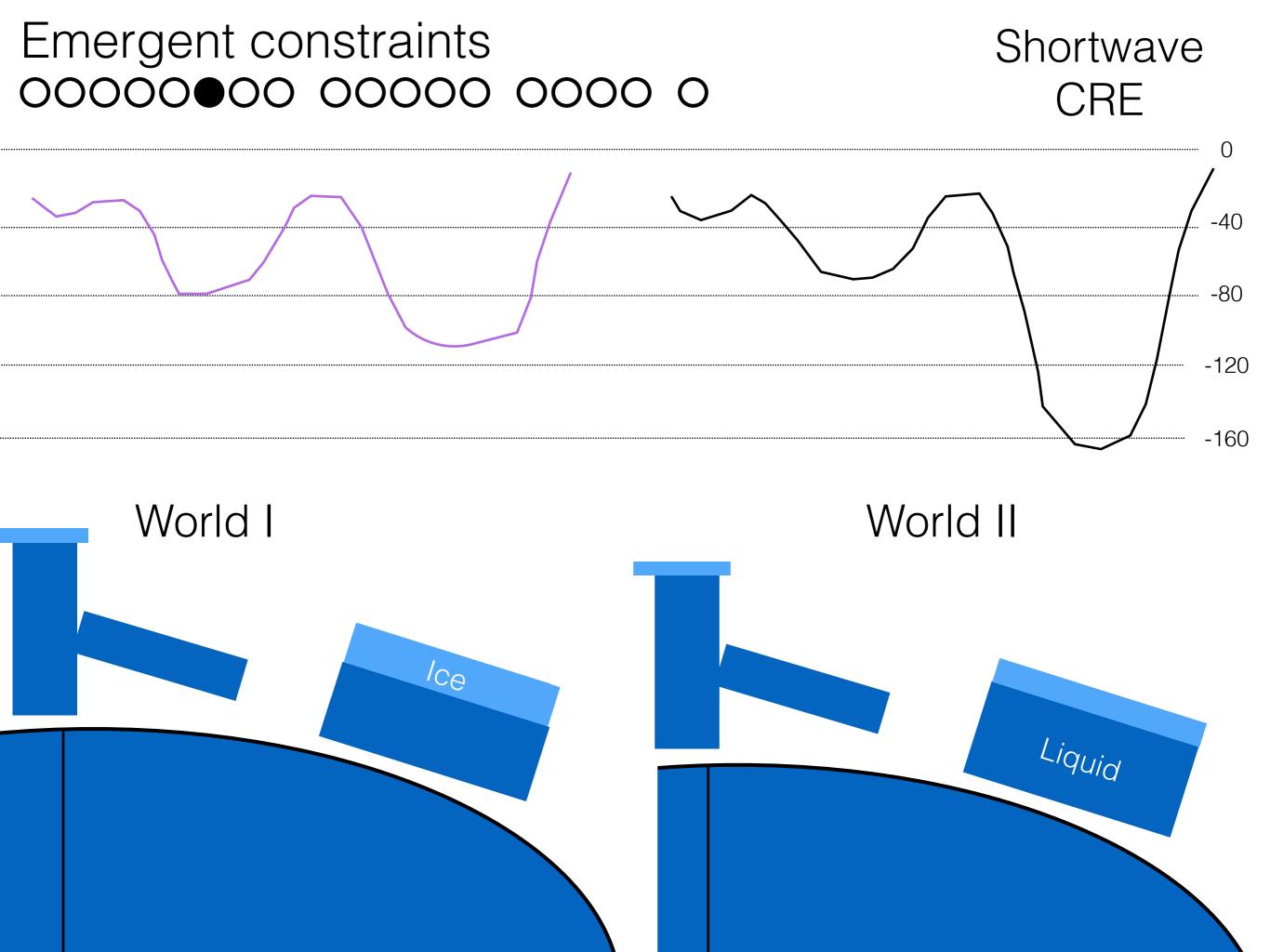


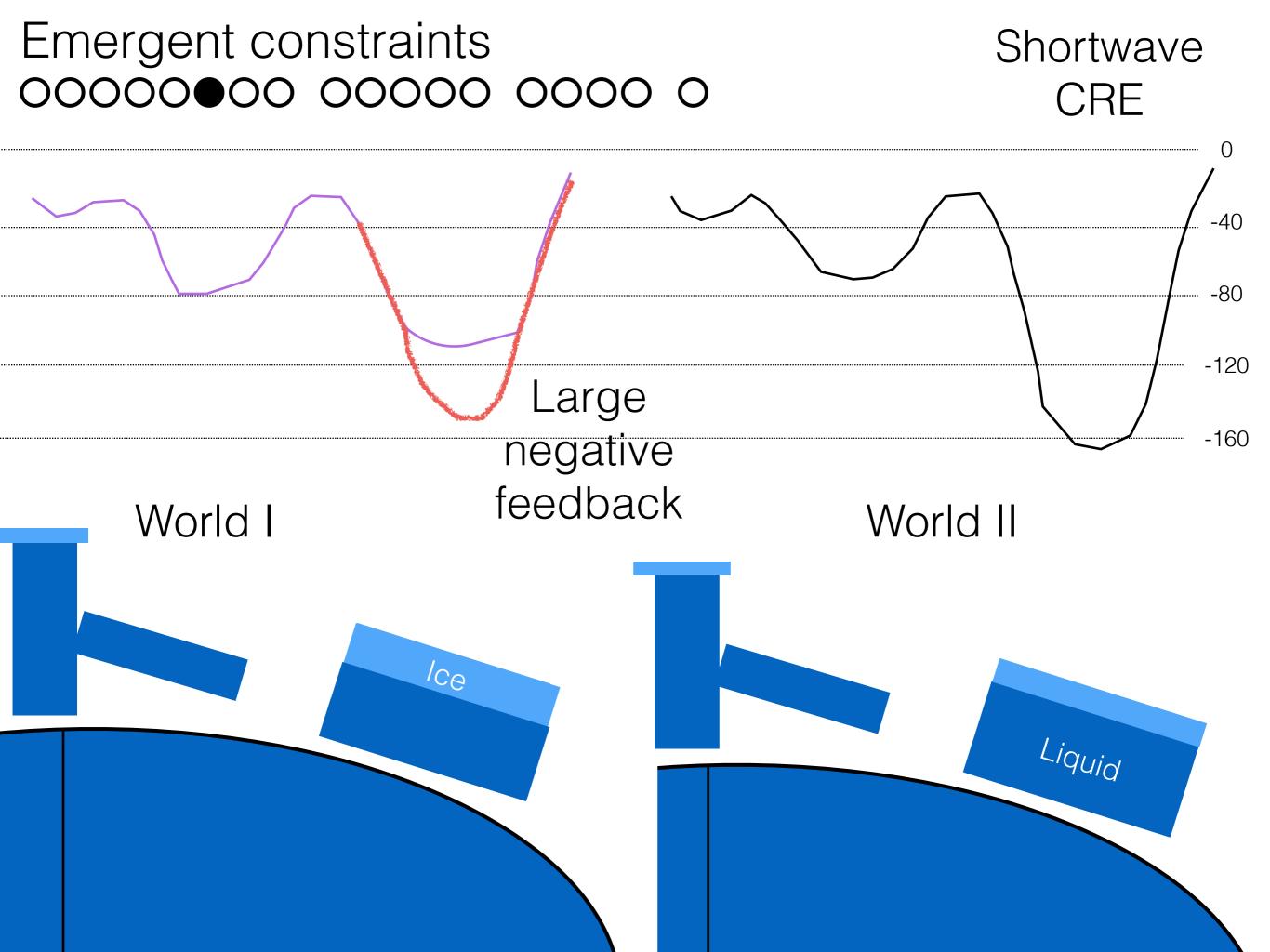


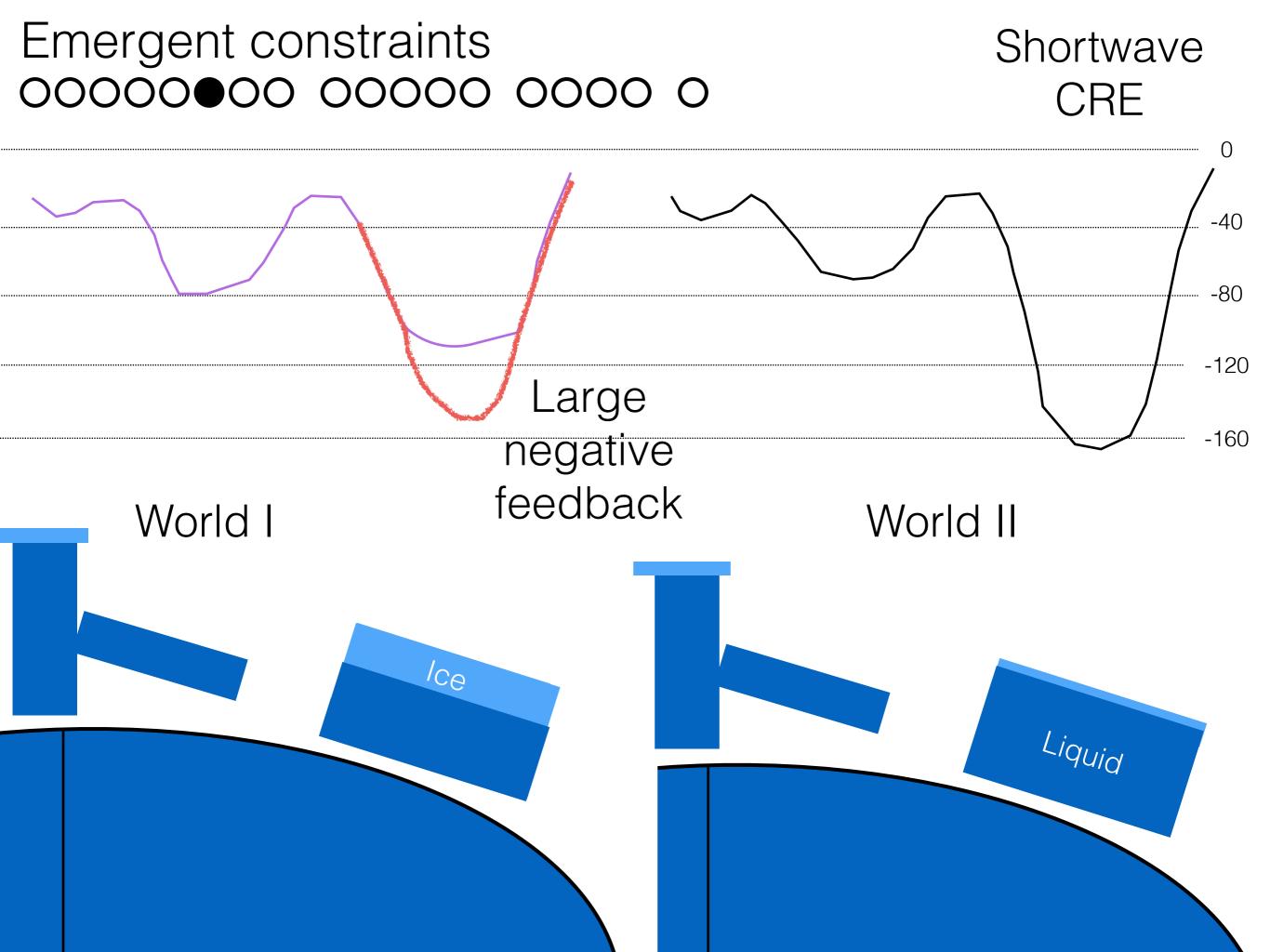


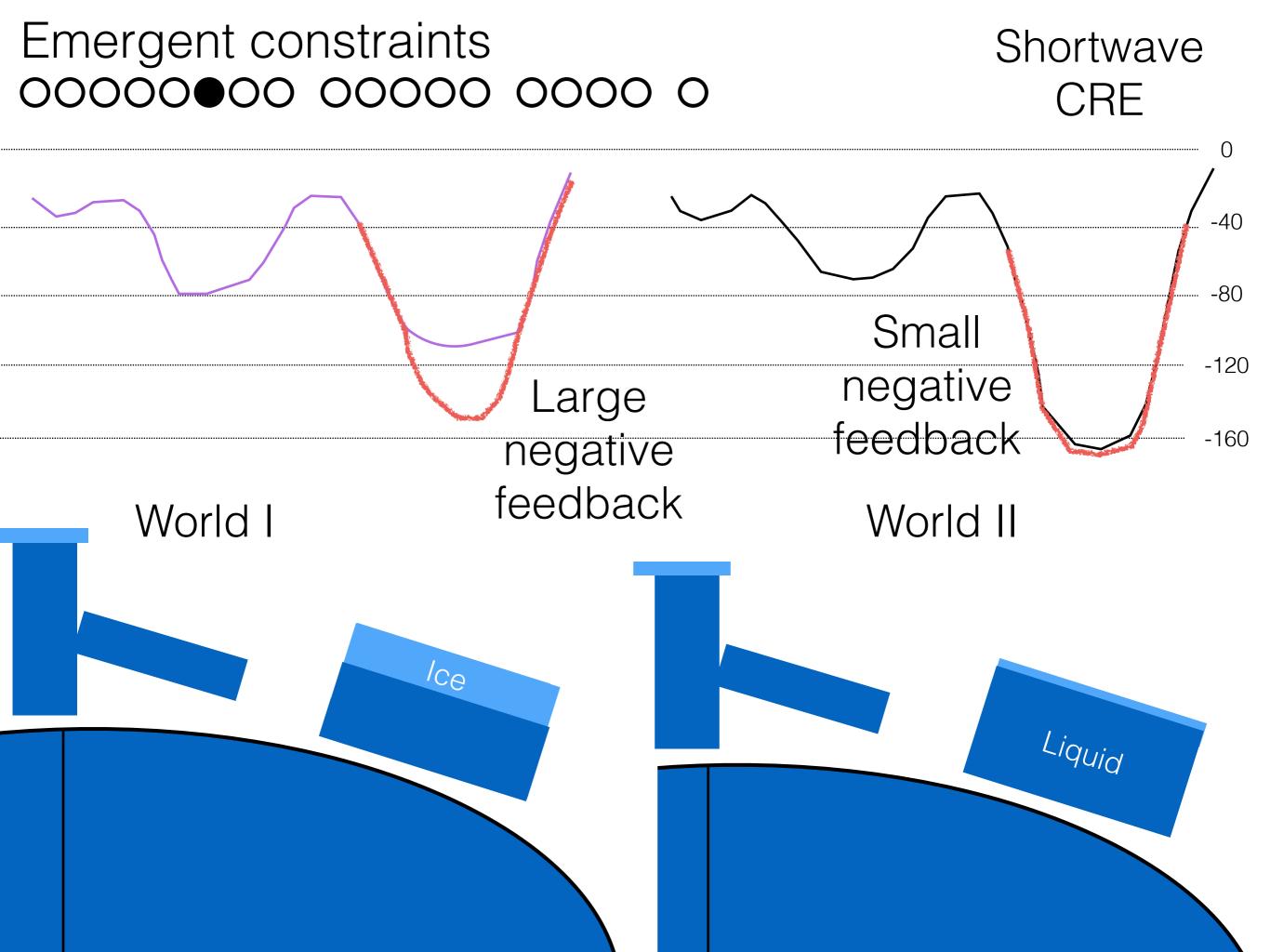


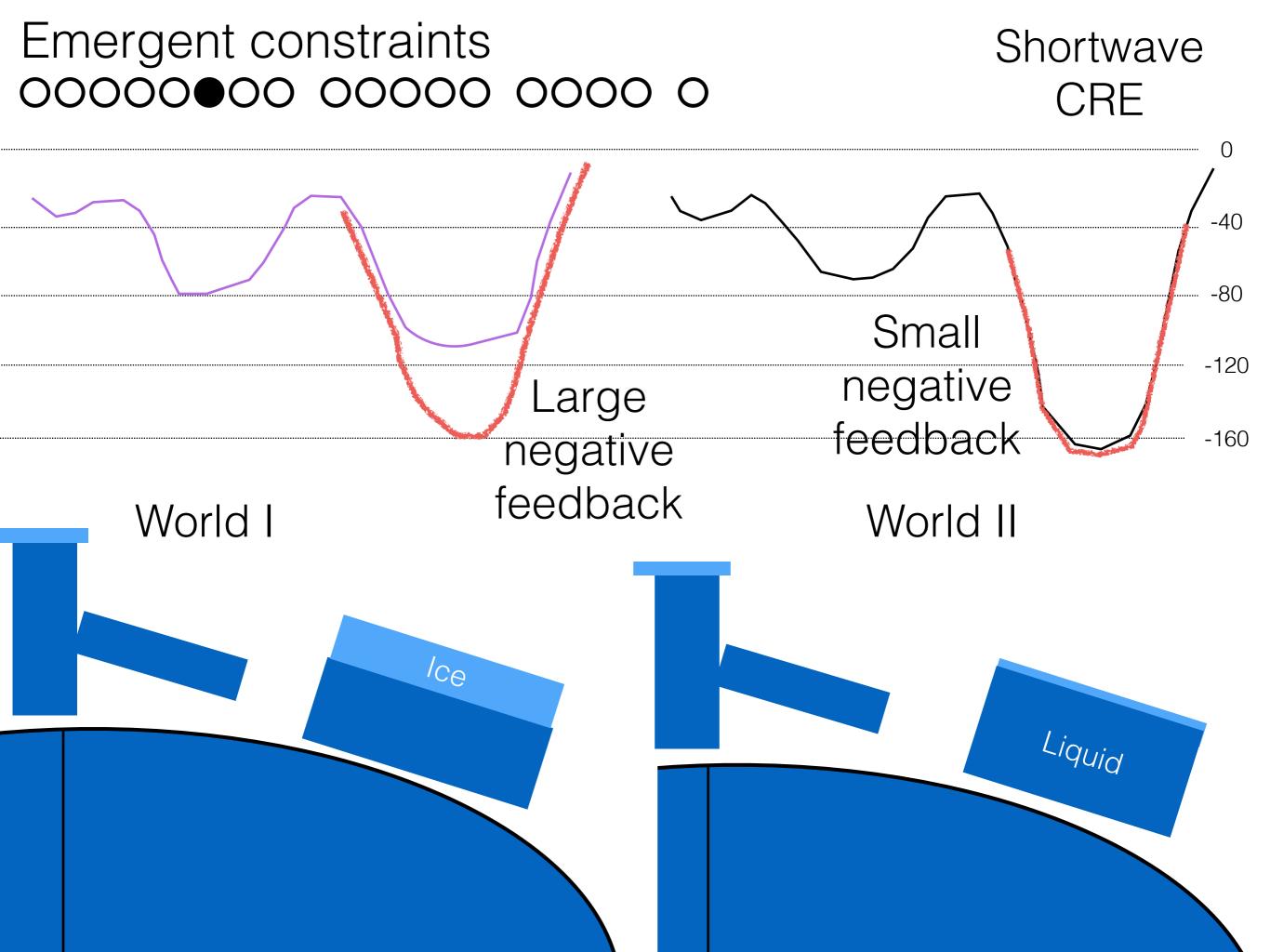


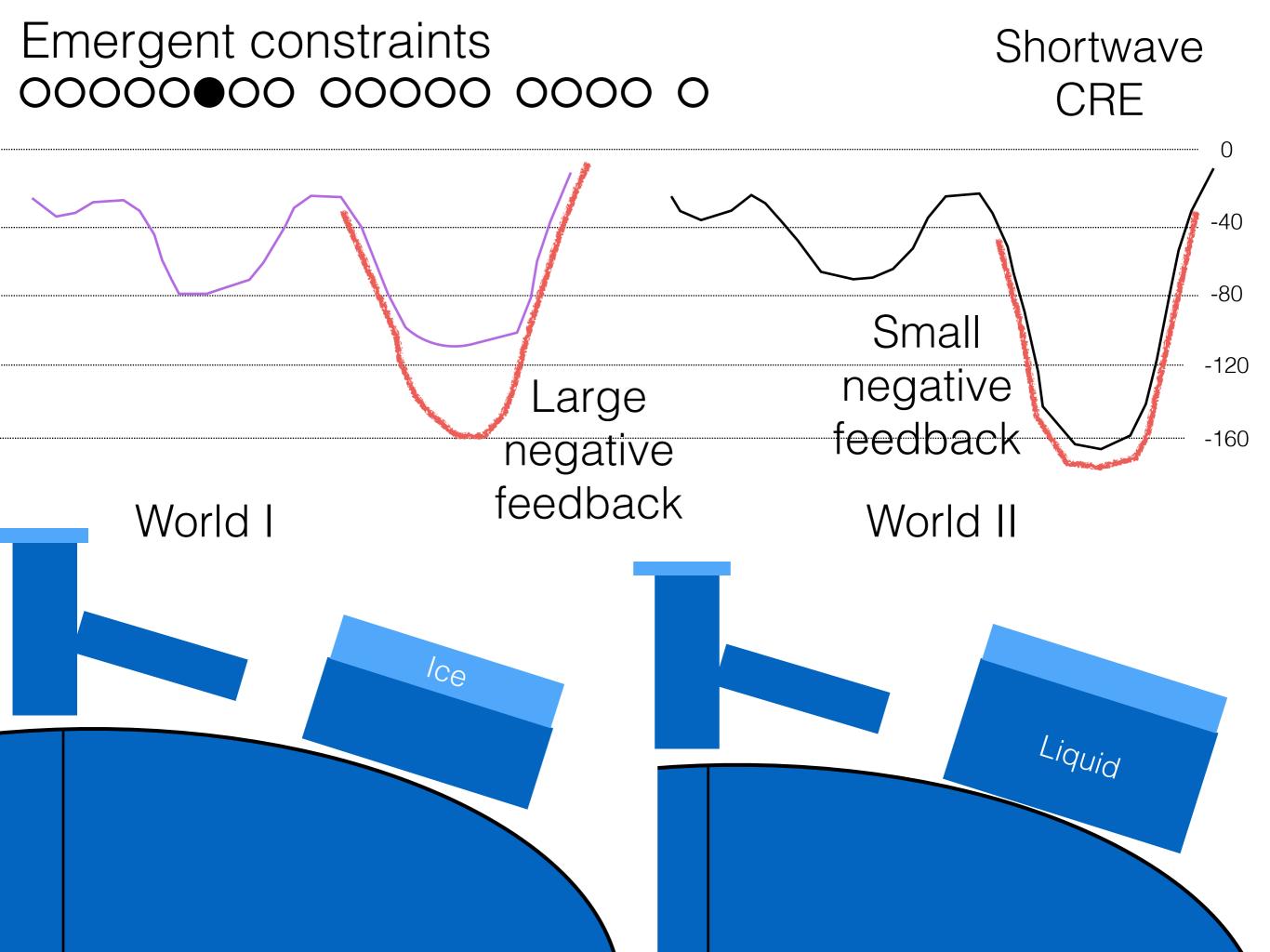




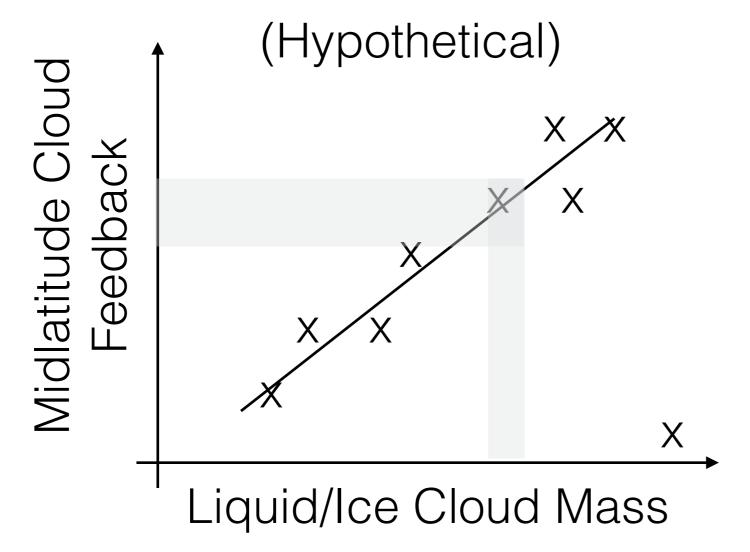








 Midlatitude clouds introduce potential constraint on cloud feedback in these regions (via analysis of reflected shortwave and liquid/ice water path)



Emergent constraints 000000 0000 0000 0

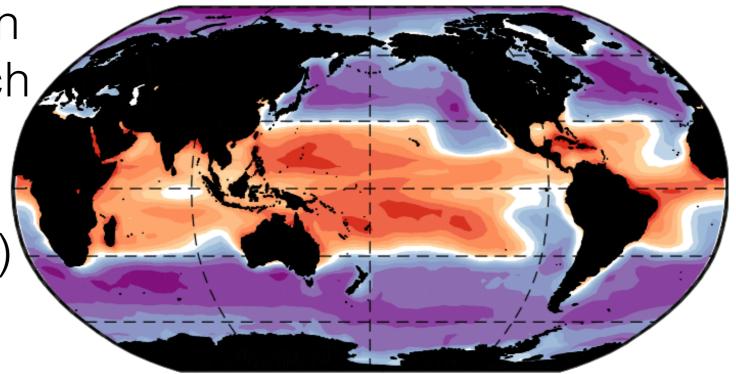
- Ice-liquid partitioning (or just mean cloud liquid water)
 (McCoy et al., 2015)
- Mean state shallow/deep mixiness (Sherwood et al., 2014)
- Tropical/subtropical relative humidity/cloudiness (Volodin, 2007; Sherwood et al., 2010; Fasullo and Trenberth, 2012; Bony and DuFresne 2005)
- Midlatitude jet shift (Grise and Polvani, 2014) or maybe not (Wall and Hartmann, 2015)

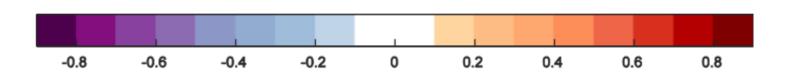
Constraint from SW CRE

- See where mean-state SW CRE projects most strongly onto the global cloud feedback (via partial least squares)
- Use AMIP models, which have same surface temperature distribution (more of an apples-to-apples comparison with observations)

Constraint from SW CRE 0000000 0 0000 0000 0

r-value between SW CRE in each model and the global cloud feedback (PLS)

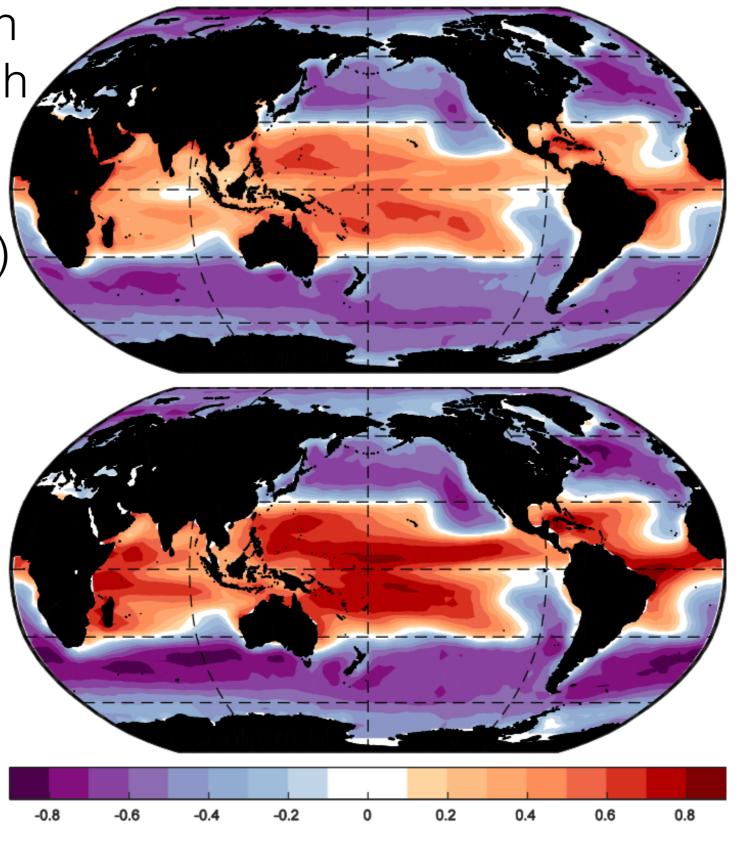




Constraint from SW CRE 0000000 0 0000 0000 0

r-value between SW CRE in each model and the global cloud feedback (PLS)

leading EOF of SW CRE



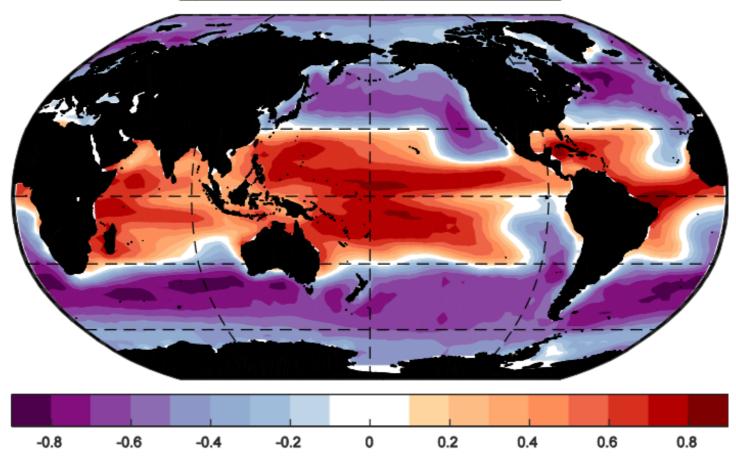
Constraint from SW CRE 0000000 0 000 0000 0

r-value between SW CRE in each model and the global cloud feedback (PLS)

r-value between EOF and PLS

exceeds 0.9

leading EOF of SW CRE



Constraint from SW CRE 0000000 0 000 0000 0

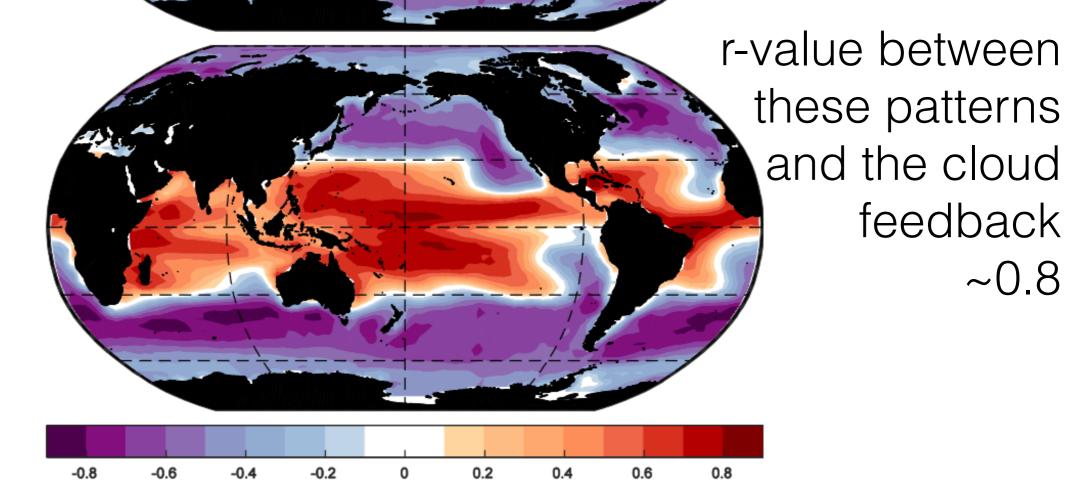
r-value between SW CRE in each model and the global cloud feedback (PLS)

r-value between EOF and PLS exceeds 0.9

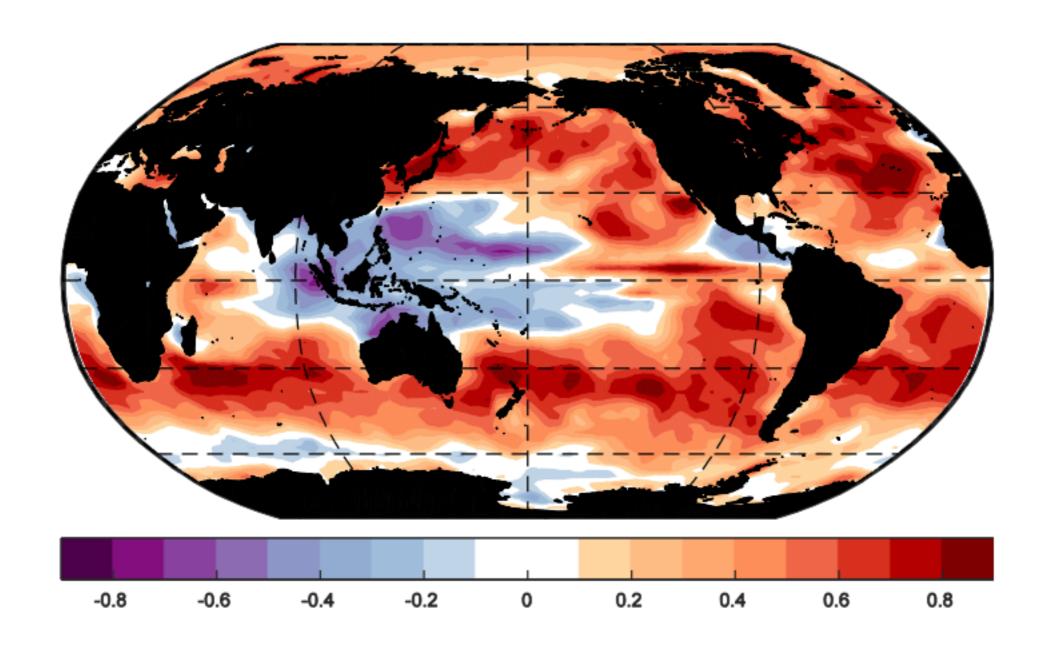
feedback

~0.8

leading EOF of SW CRE

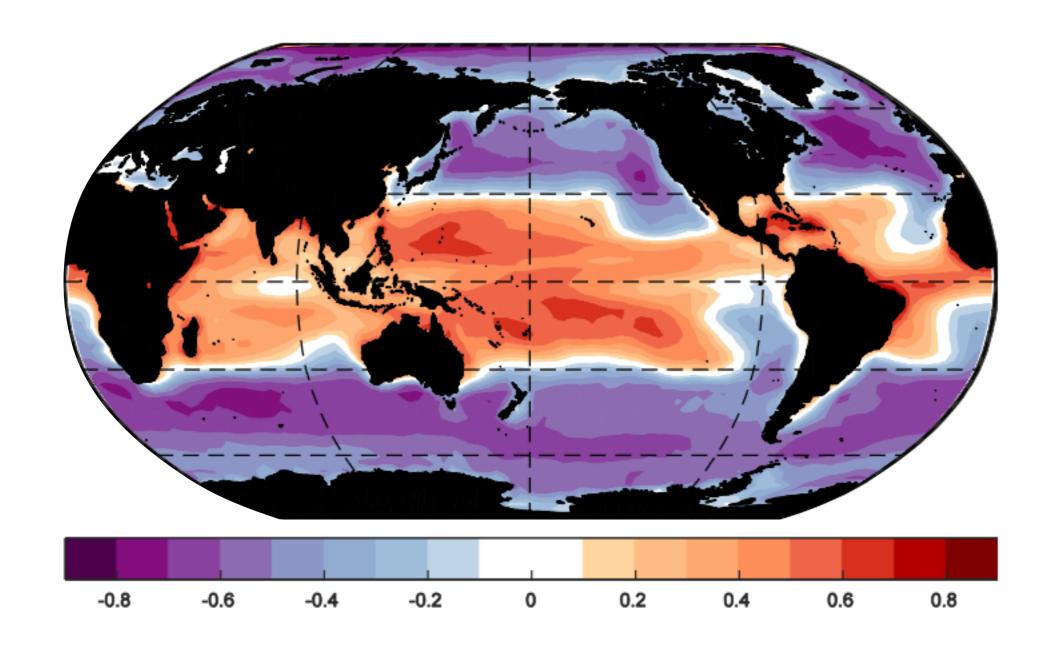


Constraint from SW CRE



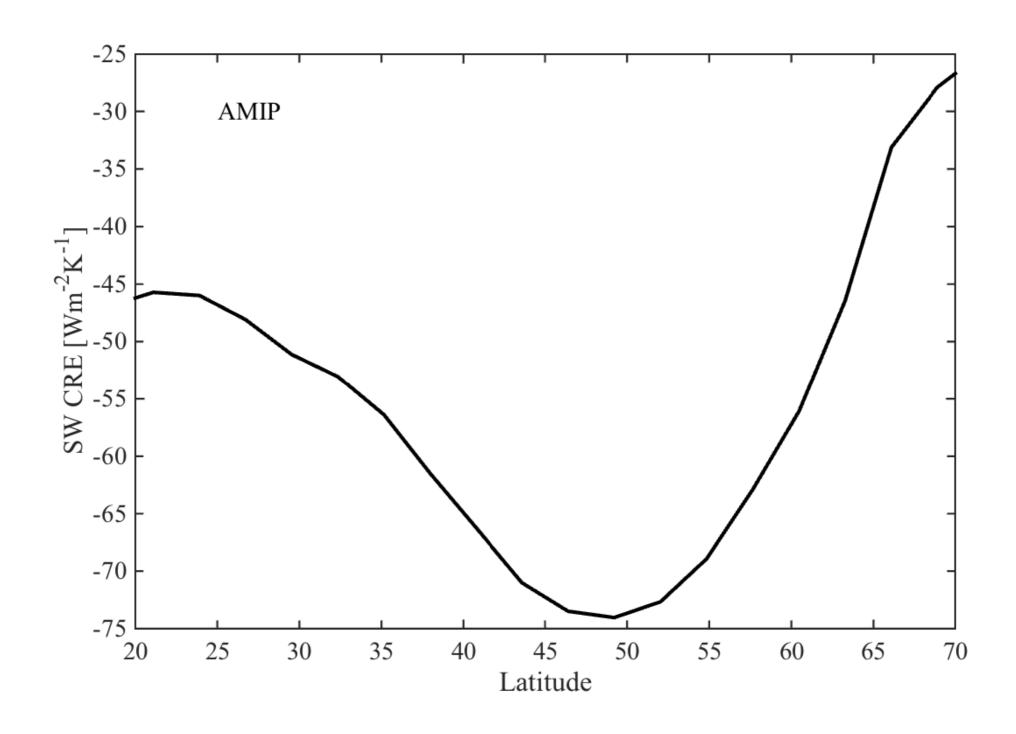
r-value between ΔSW CRE (amip4k - amip) and the global cloud feedback

Constraint from SW CRE

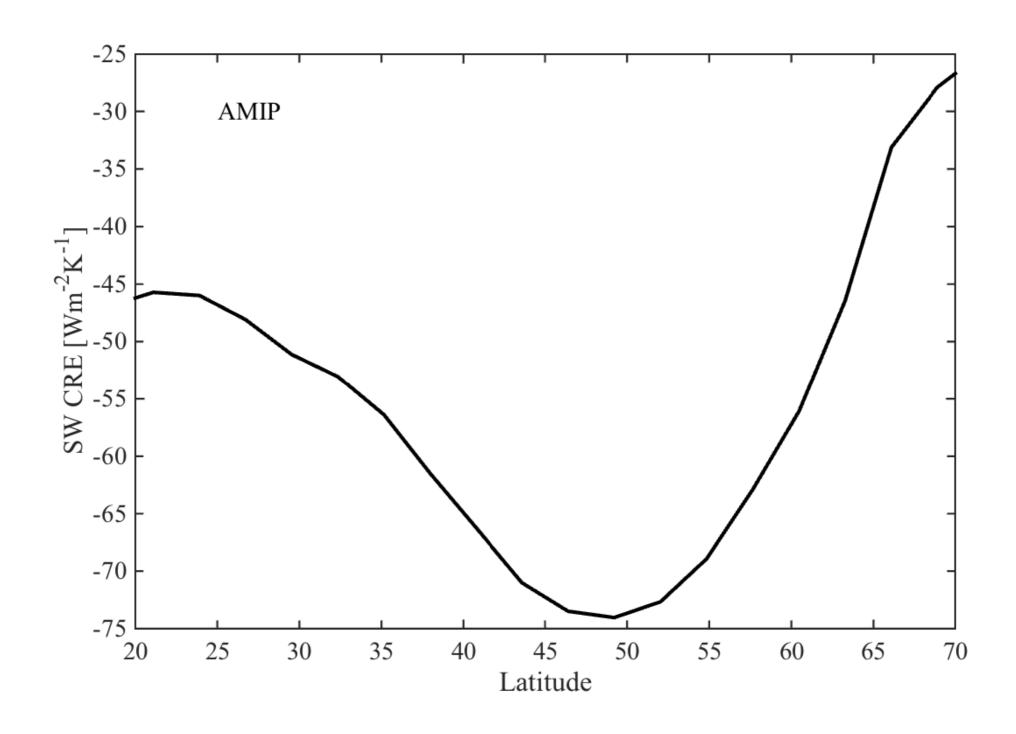


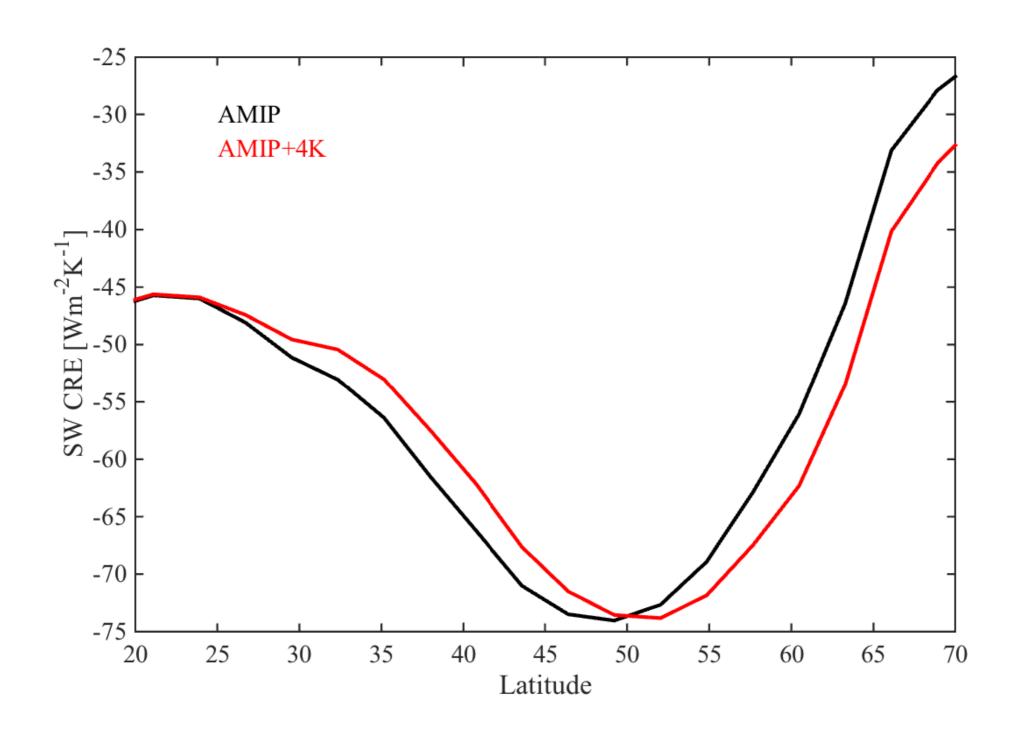
r-value between ΔSW CRE (amip4k - amip) and the global cloud feedback

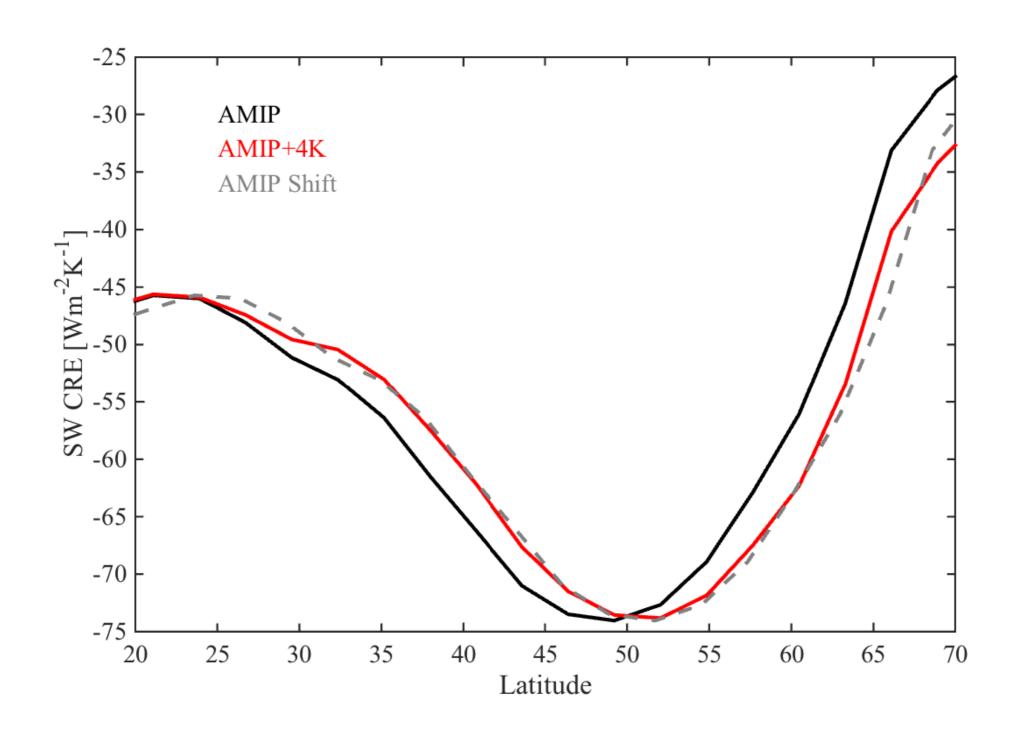
Constraint from SW CRE 0000000 0000 0000 0



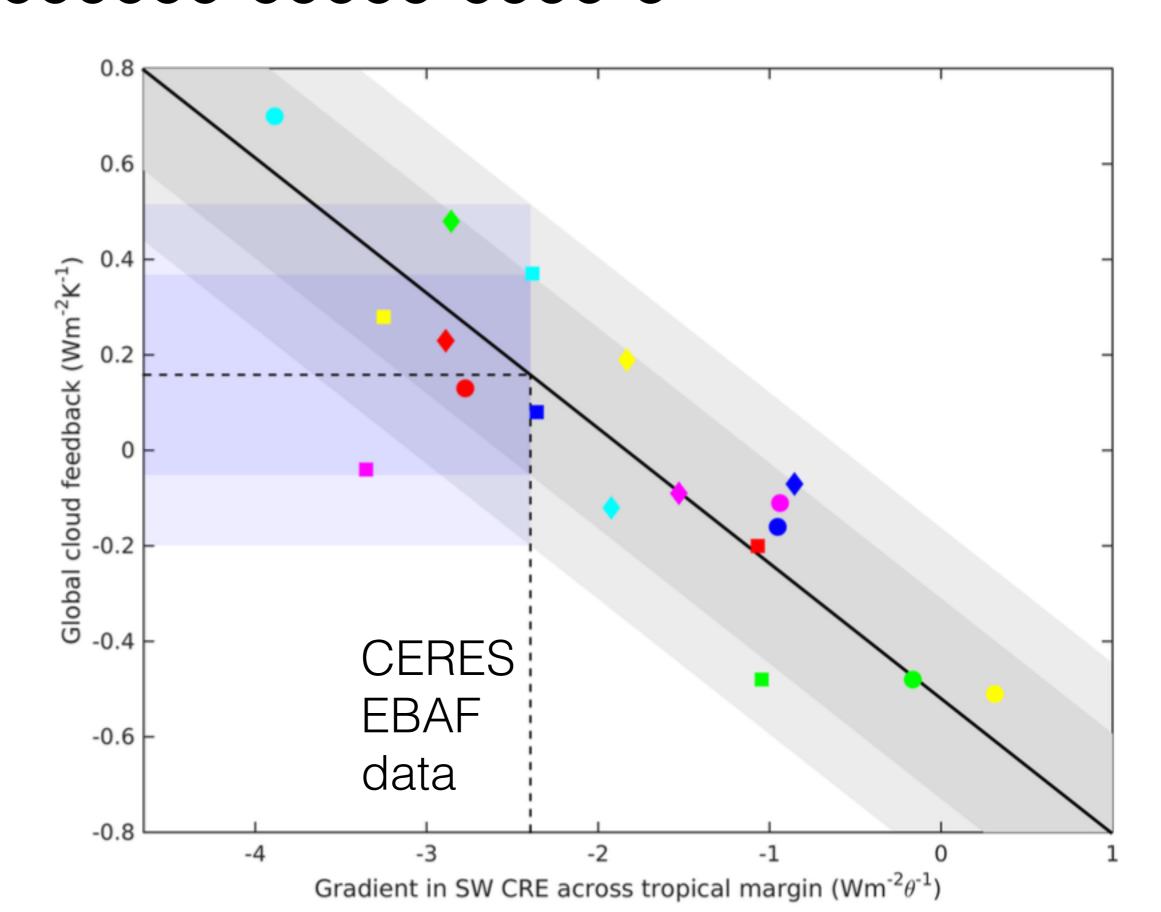
Constraint from SW CRE 0000000 0000 0000 0

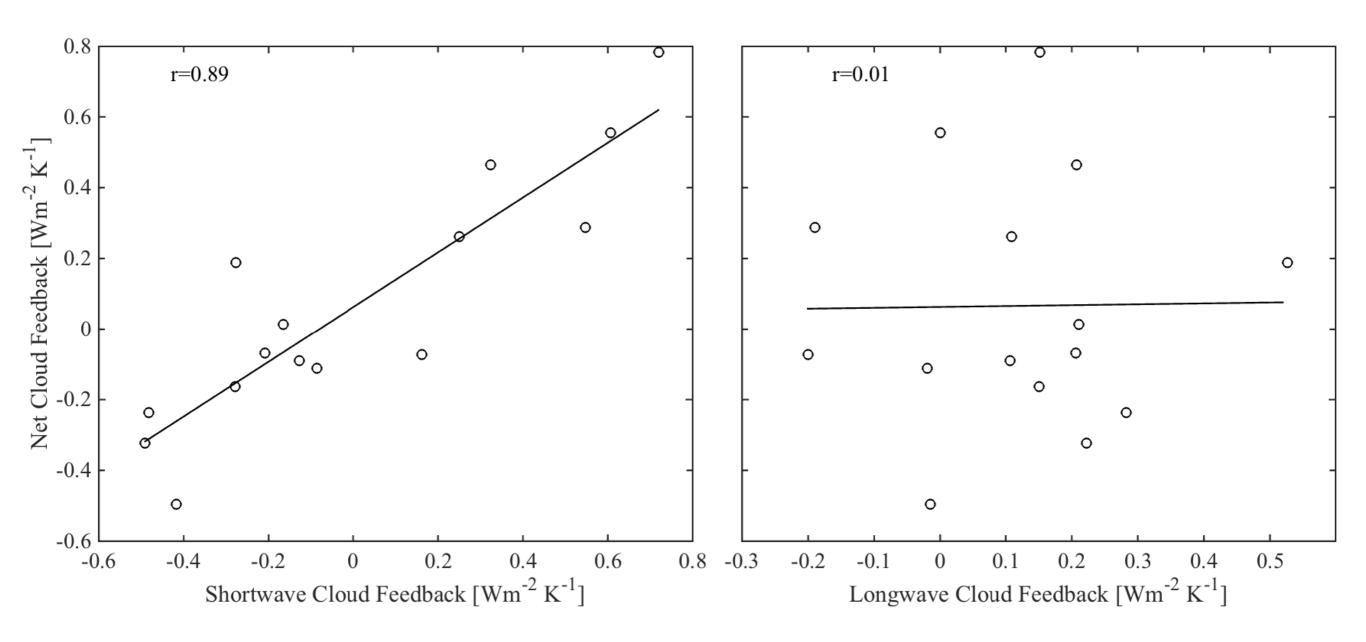




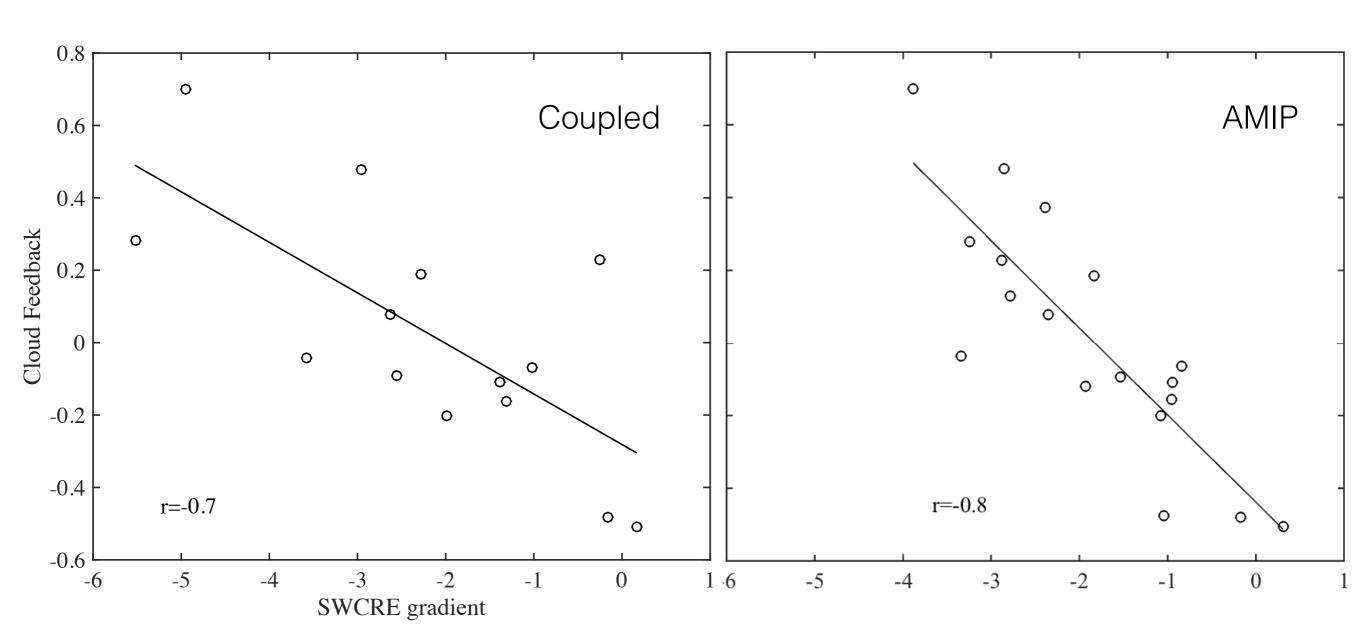


Constraint from SW CRE 0000000 0000 0000 0

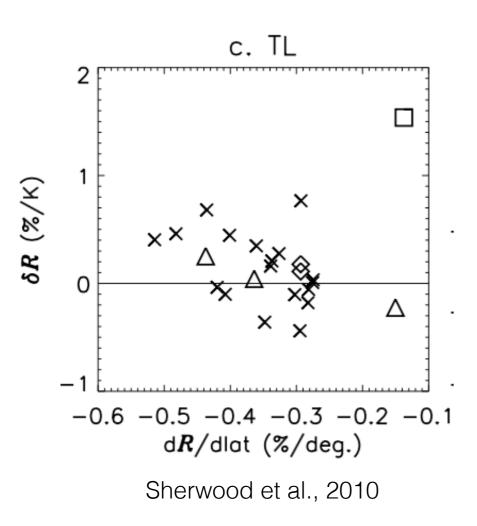




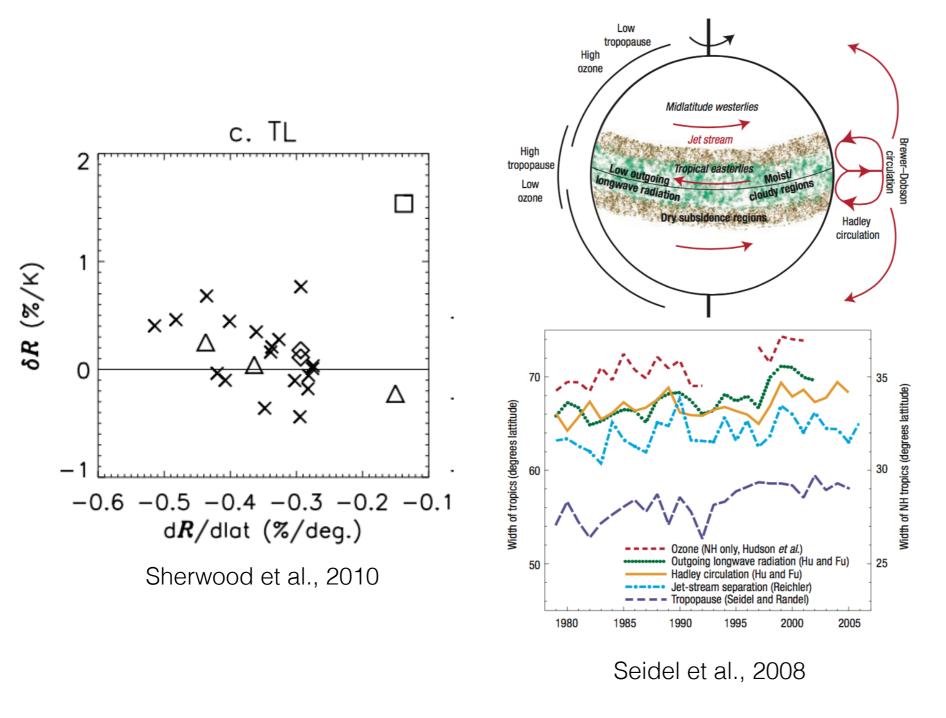
Shortwave cloud feedback dominates



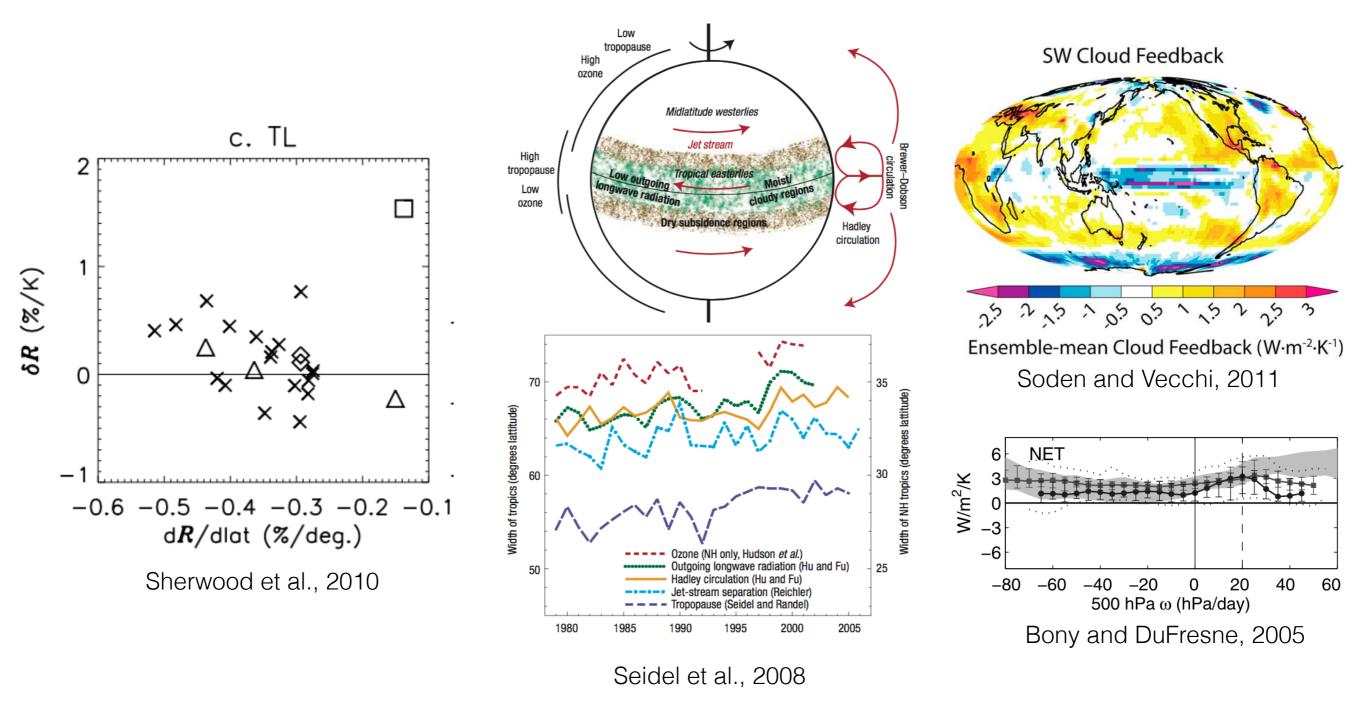
Similar relationship in coupled models, though less strong (Hadley cell edge differs ~6° across models)



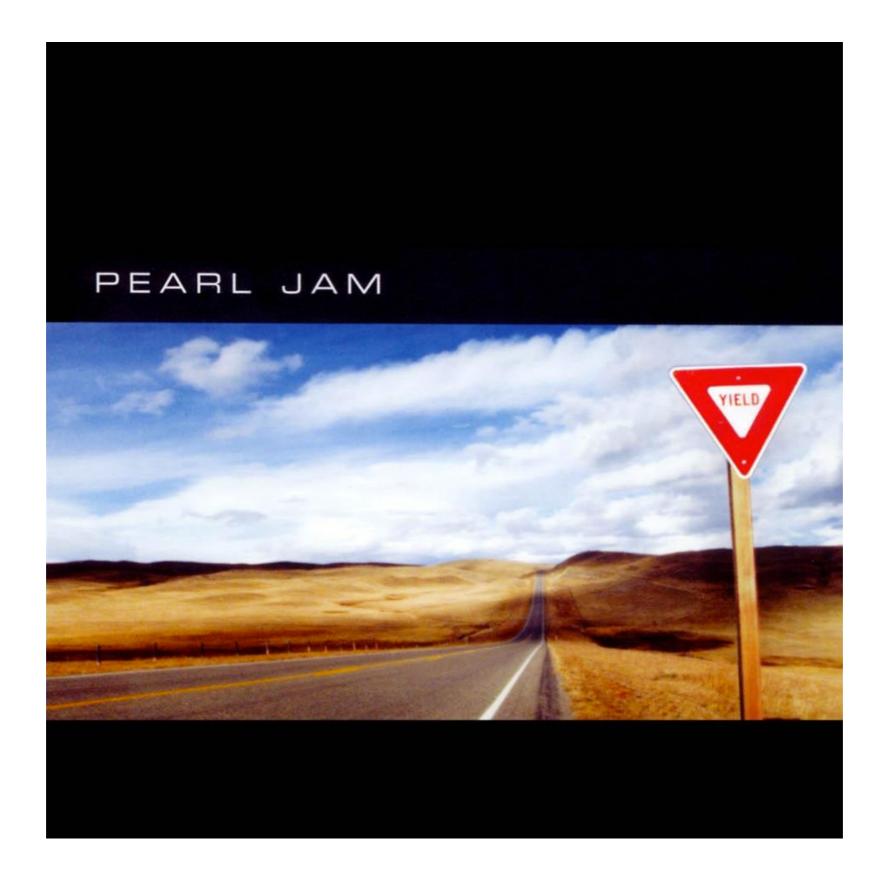
Not a new idea, but not fully assembled



Not a new idea, but not fully assembled



Not a new idea, but not fully assembled



Statistical significance of climate sensitivity predictors obtained by data mining

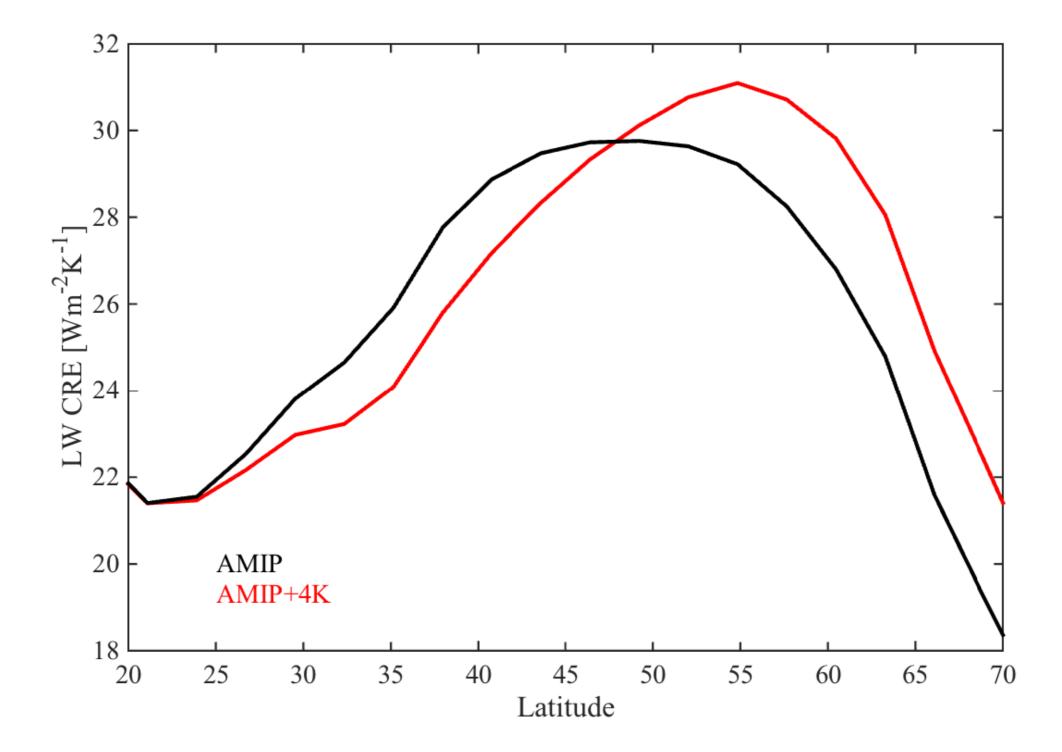
Peter M. Caldwell¹, Christopher S. Bretherton², Mark D. Zelinka¹, Stephen A. Klein¹, Benjamin D. Santer¹, and Benjamin M. Sanderson³

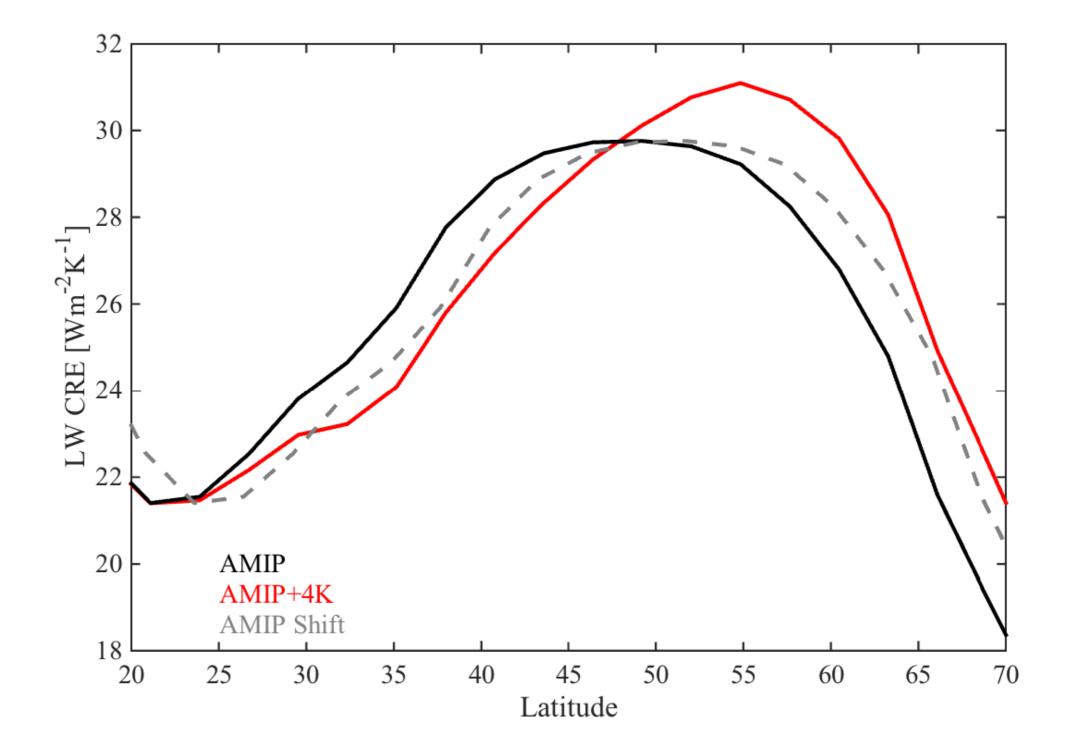
¹Lawrence Livermore National Laboratory, Livermore, California, USA, ²Department of Atmospheric Sciences, University of Washington, Seattle, Washington, USA, ³National Center for Atmospheric Research, Boulder, Colorado, USA

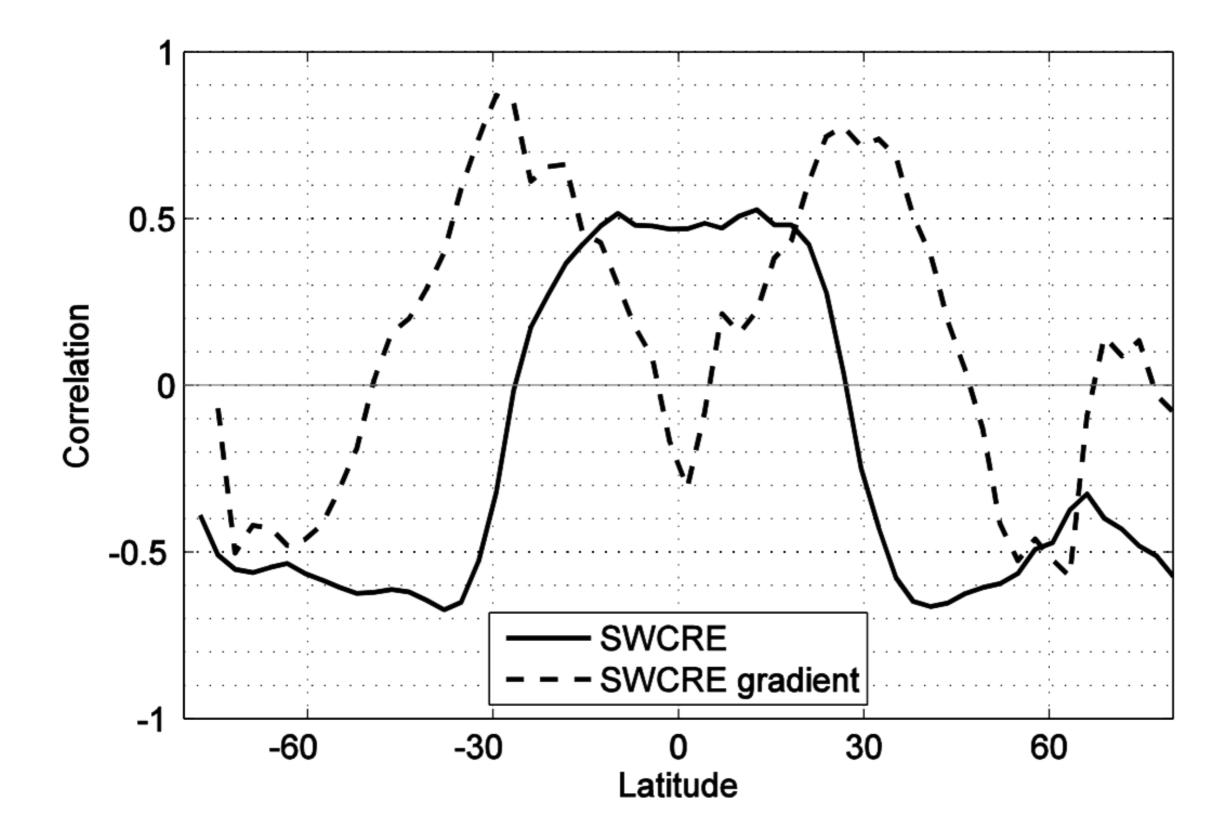
Abstract Several recent efforts to estimate Earth's equilibrium climate sensitivity (ECS) focus on identifying quantities in the current climate which are skillful predictors of ECS yet can be constrained by observations. This study automates the search for observable predictors using data from phase 5 of the Coupled Model Intercomparison Project. The primary focus of this paper is assessing statistical significance of the resulting predictive relationships. Failure to account for dependence between models, variables, locations, and seasons is shown to yield misleading results. A new technique for testing the field significance of data-mined correlations which avoids these problems is presented. Using this new approach, all 41,741 relationships we tested were found to be explainable by chance. This leads us to conclude that data mining is best used to identify potential relationships which are then validated or discarded using physically based hypothesis testing.

Summary 0000000 0000 0000 •

- AMIP models allow close spatial comparison of models
- Dipole in mean state SW CRE explains over 60% of cloud feedback
- Results suggest this is due to a expansion of the Hadley cell that shifts mean state SW CRE
- Variance in cloud feedback explained by gradient in SW CRE across subtropical margin
- CERES data suggests models with larger cloud feedbacks are closer to reality



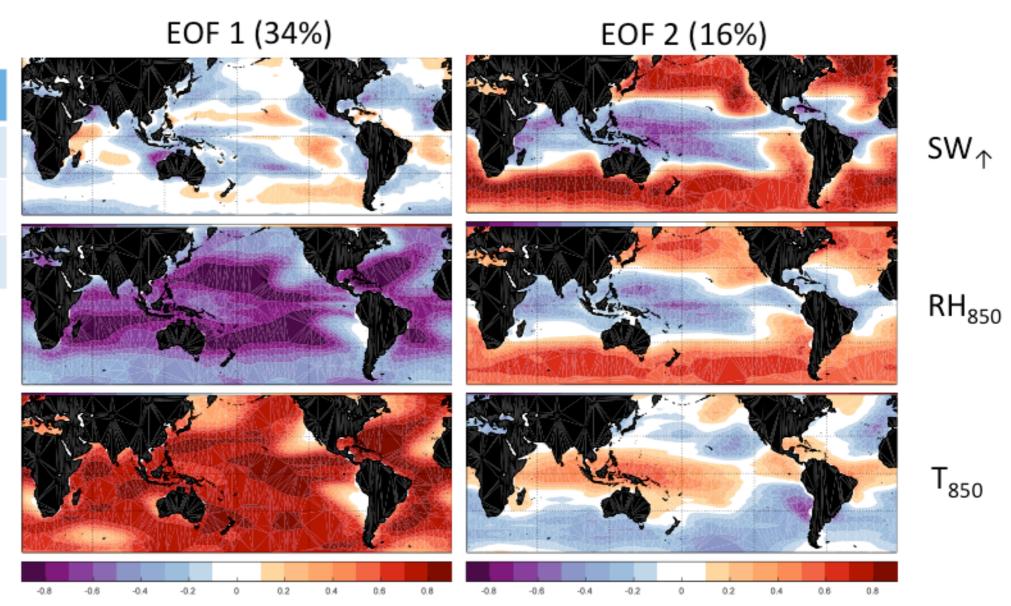




Correlation table

| | PC 1 | PC 2 |
|----------|------|------|
| ECS | .67 | .56 |
| Cloud FB | 04 | .76 |
| CS FB | .60 | 06 |

- EOF 1 is related to Clear-sky feedback (contradicts Sherwood)
- EOF 2 is related to Cloud feedback



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